A New Hybrid Adaptive Filtering Approach for ECG Noise Reduction with Low Complexity Design

Abdulhamed M Jasim[1,3], Ekenedirichukwu N Obianom[2], Noor Qaqos[1], Shamsu Idris Abdullahi[1], Fan Feng[1], G Andre Ng[2], Xin Li[1]

[1]School of Engineering, University of Leicester, Leicester, UK
[2]Department of Cardiovascular Sciences, University of Leicester, Leicester, UK
[3]College of Electronics Engineering, Ninevah University, Mosul, Iraq

Abstract

Frequency-based ECG denoising methods often distort QRS morphology when suppressing noise in P and T waves. Strong smoothing helps reduce noise but may lose important features, highlighting the need for morphology-preserving denoising techniques. This study proposes a hybrid adaptive filtering approach to remove EMG noise while preserving ECG features with low complexity. Parallel adaptive low-pass filters were used: one targeting P and T waves (10-25Hz) and another for the QRS complex (30-70Hz). Filtered outputs were combined, and transition points were smoothed using an adaptive Savitzky-Golay filter. Evaluation was done on the SimEMG database. Performance was compared to methods using the same database: adaptive wavelet Wiener filtering (AWWF), wavelet transform (WT), finite impulse response (FIR), and iterative regenerative method (IRM). For signals with SNRin < 4dB, the proposed method achieved 10.37 dB SNR improvement, outperforming IRM (10.31dB), AWWF (9.23 dB), WT (4.59 dB), and FIR (4.19 dB). At SNRin = 4-8 dB, it reached 10.05 dB, maintaining superior results. The method continued to show improvement for higher SNR levels (≥16 dB). The average correlation coefficient was 98.29%, indicating strong signal preservation. Results demonstrate the method's effectiveness in suppressing EMG noise while maintaining ECG morphology.

1. Introduction

An electrocardiogram (ECG) is a non-invasive tool that records the heart's electrical activity using electrodes on the skin. It provides key information for assessing heart rhythm, conduction, and overall function[1]. ECG features help detect various heart disorders. However, ECG signals are often contaminated by noise such as baseline wander (BW), powerline interference (PLI), and muscle activity (EMG) noise. These distortions can affect, especially low-amplitude waves like P and T, reducing diagnostic accuracy. Therefore, effective denoising methods are needed to preserve ECG shape and clinical value. Filtering ECG signals is challenging, especially when noise overlaps with the signal's frequency range. Many techniques have been proposed[2-7] including wavelet transforms (WT), empirical mode decomposition (EMD), adaptive filters, and neural networks. Although effective, these methods have trade-offs. Frequency-based methods, for example, may smooth important details or distort the QRS complex. This emphasizes the necessity for effective denoising methods, preserving the crucial ECG features without affecting the morphology. In this work, we propose a hybrid adaptive filtering method to reduce EMG noise while maintaining ECG features. The method is simple and suitable for practical use. The paper is organised as follows: Section 2 introduces an overview of the theoritical background for Butterworth and Savitzky-Golay filters. Section 3 details the methodology. Section 4 shows results. The evaluation and conclusion are presented in sections 5&6, respectively.

2. Theoretical Background

2.1. Butterworth Filter

The Butterworth filters are designed to offer a smooth transition to the stop-band and a flat frequency-response. the transfer function can be defined in Eq. (1)[8]:

$$H(z) = \frac{\sum_{i=0}^{N} b_i z^{-i}}{1+\sum_{j=1}^{M} a_j z^{-j}} \quad (1)$$

Where bi and aj: feedforward and feedback coefficients respectively, and N=M: order of the filter.

In this study, 4th-order Butterworth infinite impulse response (IIR) high-pass filter and two adaptive low-pass filters were used to balance noise reduction and computational cost. The first filter, a 4th-order HPF with Fc = 0.4 Hz, was applied to remove the BW. Next, two 4th-order LPFs were used in parallel to clean the ECG morphology. This helps to suppress noise in the ECG components separately.

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2.2. The Savitzky-Golay (S-G) Filter

The Savitzky-Golay (S-G) filter smooths signals while preserving key features and reducing high-frequency noise [9]. In this work, it was used to smooth fluctuations at the boundaries after ECG reconstruction, helping maintain morphology for more accurate clinical interpretation. The filter adapts a polynomial of degree (d) to a window of ($2m$+1) points by applying the following minimization:

$$\min_{a_0,a_1,\ldots,a_d} \sum_{k=-m}^{m}\left(y[n+k]-\sum_{j=0}^{d} a_j k^j\right)^2 \quad (2)$$

Where a_j = polynomial coefficients and $y[n+k]$ = data points, whereas $k \in [-m, m]$. The convolution $y[n]$ is:

$$y[n] = \sum_{k=-m}^{m} c_k \; y[n+k] \quad (3)$$

Where ck represent pre-computed coefficients that are based on window size and polynomial degree.

3. Methodology

3.1. Proposed Method

The proposed ECG denoising method uses hybrid digital filters that balance performance and computational complexity. As shown in Fig.1, 4th order Butterworth HPF with a cut-off frequency of 0.4 Hz is first applied to remove the BW noise, which can be caused by different factors such as respiration. This is a common pre-processing step to keep the recorded ECG signal aligned with the baseline. It removes the BW noise without affecting the low-frequency components in the ECG signal. Two parallel adaptive 4th order Butterworth low-pass filters (LPFs) are used to smooth different parts of the ECG signal. Both share the same type and order but target different frequency bands. LPF_1 (cut-off located in a range of 10–25 Hz) enhances P and T waves but may distort the QRS complex. LPF_2 (cut-off located in a range of 30–70 Hz) preserves the QRS complex but is less effective on P and T waves.

These ranges vary due to the clinical diversity in the ECG database. The cleaned ECG components at the outputs of both adaptive low-pass filters are then carefully combined to reconstruct the ECG signal. To address discontinuities at the boundaries between P-to-QRS and QRS-to-T segments caused by the differing cut-off frequencies, the reconstructed signal is smoothed using an adaptive S-G filter [10]. This filter uses a fixed polynomial order and an adjustable window size to adapt to signal variations across patients. It performs local polynomial fitting, to reduce noise while preserving essential ECG morphology. This hybrid method, combining Butterworth filtering, selective reconstruction, and adaptive smoothing, addresses spectral overlap between EMG noise and ECG components with a low complexity design. Table 1 summarizes the denoising steps.

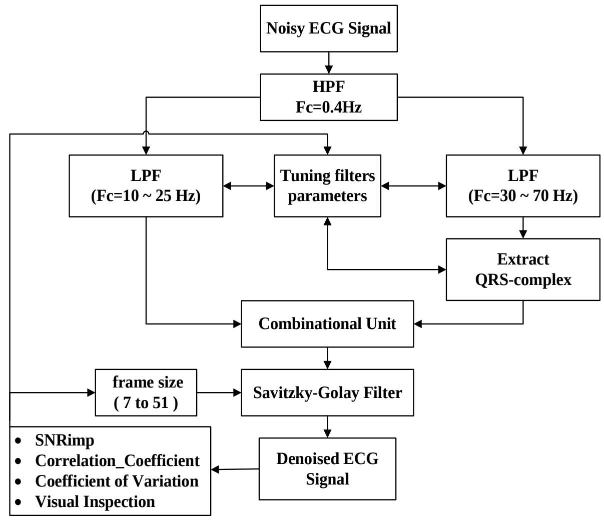

Figure 1. Flowchart of the Proposed ECG Denoising Method.

Table 1. Proposed ECG denoising algorithm.

Step	Description
1	Load the ECG signal.
2	Apply a high-pass filter (HPF) with a cut-off frequency of 0.4 Hz to remove the BW noise. In
3	parallel, apply two low-pass filters: -Apply a LPF1 with a cut-off frequency range of 10–25 Hz to clean the P-wave and T-wave components (note: this distorts the QRS). -Apply a LPF2 with a cut-off frequency range of 30–70 Hz to clean the QRS complex components (note: P/T waves remain noisy).
4	Extract the clean QRS components from LPF2 by detection R peaks using amplitude and refractory constraints (we used a `findpeaks` function in MATLAB) to ensure reliable identification of QRS complexes.
5	Carefully integrate the extracted QRS complex components from LPF2 with the clean P-wave and T-wave components from LPF1.
6	Apply a S-G filter to smooth transitions and minimize discontinuities.
7	Evaluate performance using various metrics.
8	Repeat steps 3–7 to improve the results. END

3.2. Dataset

In this paper, the performance of the proposed denoising method was tested based on the SimEMG database [3]. It is a recent database that provides recorded ECG signals with and without EMG noise. This database contains 37 noise-free and 110 noise-contaminated single-lead, which were recorded from 14 subjects in the real environments (5 males and 9 females aged 40 ± 13). Frequency sampling of this database is 500Hz.

4. Performance Evaluation Metrics

To evaluate the performance of the proposed ECG denoising method, different quantitative metrics were used. These included the Signal-to-Noise Ratio Improvement (SNRimp), Eq. (4), which refers to the enhancing in signal quality after denoising process; the standard deviation (SD), which means how much individual values in a dataset differ from the mean value, the coefficient of variation (CV), which can be calculated by (SD/mean value), where it can help quantify signal stability before and after filtering process, and the Pearson correlation coefficient CC , refers to how strongly two signals are linearly related. These metrics provide a comprehensive evaluation of the accuracy. Therefore, lower values of SD and CV and higher values of SNRimp and ρ indicate better performance of the proposed model.

$$SNR_{imp} = SNR_{out} - SNR_{in} \quad (4)$$

Regarding the morphology preservation, the correlation coefficient metric was calculated between the denoised signal (A) and the noise-free signal (B) as:

$$\mathrm{CC}\ (\mathrm{A},\mathrm{B}) = 100 \times \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i-\mu_A}{\sigma_A}\cdot\frac{B_i-\mu_B}{\sigma_B}\right) \quad (5)$$

where μ_A, and μ_B are the mean values and σ_A, and σ_B are the standard deviation (SD) values for the noise-free and filtered signals, respectively.

5. Simulation Results

In this section, the simulation results of the suggested denoising approach are presented using the SimEMG database, Since EMG noise overlaps with ECG frequencies, removing it without distorting key features is challenging. All ECG recordings in the database were tested. The noisy recordings were categorized into six groups based on noise levels using SNRi, which are (<4, 4~8, 8~12, 12~16, 16~20, >20). Figure 2 shows the denoising process. The QRS complexes filtered by LPF_2 (see Fig. 2(b)) are carefully reintegrated (see Fig. 2(c)) into the denoised P-wave and T-wave from the LPF_1 (see Fig. 2(a)). The final step uses the S-G filter to smooth boundary discontinuities (see Fig. 2(d)). The proposed hybrid approach preserves ECG morphology and enhance clinical interpretability. Figure 3 illustrates the ECG denoising steps, which reflect the performance of the proposed work. To further assess performance, the correlation coefficients (CC) between reference and denoised signals were computed across all ECG recordings. Figure 4 shows the average CC values.

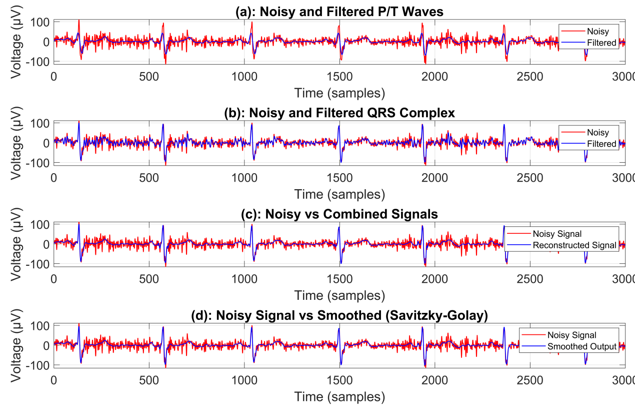

Figure 2. Denoising Steps reflect the performance of the proposed method.

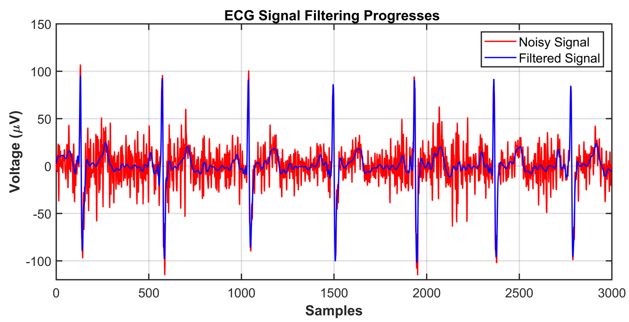

Figure 3. Noisy and denoised ECG signal obtained using the proposed filtering method for EMG artifact removal.

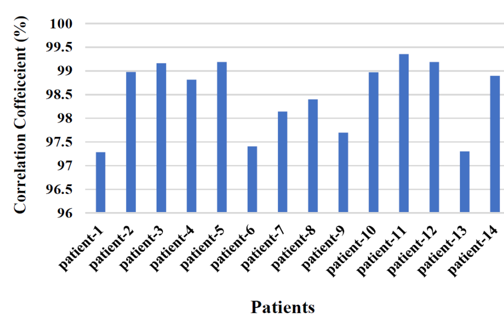

Figure 4. The correlation coefficients across all patients

6. Comparisons

This section evaluates the performance of the proposed ECG denoising method by comparing it with other techniques using the SimEMG database. The assessment uses three metrics: the SNRimp, the SD, and the CV. Higher SNRimp and lower SD and CV values indicate better denoising. We compared our method's performance against IRM [3], AWWF [6], WT [4], and FIR [11], all tested on this database. Table 2 shows SNRimp average values across SNRin groups. On average, the proposed method achieves higher SNRimp values than others, showing superior performance at most noise levels. The

SD and CV are also used to compare consistency. The lower values reflect more reliable performance. Together, these metrics provide a clear view of denoising effectiveness and consistency across methods. Table 3 presents a comparison of the CV values across different noise-level groups. The proposed method achieved the lowest CV in the majority of groups, demonstrating its superior stability and robustness. Moreover, the overall average CV of the proposed method was the lowest among all compared techniques, further confirming its consistent performance across varying ECG signal qualities.

Table 2. The SNRimp over various denoising methods

SNRin	IRM	AWWF	WT	FIR	Proposed-method
< 4	10.31	9.23	4.59	4.19	**10.37**
4 - 8	10	8.57	3.84	3.83	**10.05**
8 - 12	**7**	6.27	2.15	3.18	5.87
12 - 16	**5.17**	4.57	-1.41	2.17	4.52
16 - 20	3.36	3.26	-2.38	1.45	**3.38**
> 20	1.32	2.14	-7.18	0.22	**1.97**

Table 3. The coefficient of variation values over various denoising methods

SNRi	IRM	AWWF	WT	FIR	Proposed-method
<4	0.25	0.23	0.24	0.17	**0.16**
4 - 8	0.30	0.28	0.29	0.29	**0.15**
8 - 12	0.29	0.29	0.70	**0.25**	0.27
12 - 16	0.56	0.46	1.84	0.51	**0.27**
16 - 20	0.48	0.40	0.88	0.55	**0.38**
>20	0.00	0.00	0.00	0.00	0.00
Average	0.31	0.28	0.66	0.29	**0.21**

7. Conclusion

In this study, a hybrid adaptive filtering method for ECG denoising was proposed to effectively remove the EMG noise. It combines two parallel Butterworth LPFs, targeting P/T waves (10-25 Hz) and QRS complexes (30-70 Hz), with an adaptive Savitzky-Golay filter to smooth segment transitions. Evaluated on the SimEMG database, the proposed approach achieved an SNRimp of up to 10.37 dB in low-SNRin scenarios, outperforming IRM, AWWF, WT, and FIR techniques. Additionally, it showed the lowest coefficient of variation among all methods, confirming its stability. The average correlation coefficient of 98.29% further reflects strong morphological preservation. These findings demonstrate that the proposed method provides a robust and efficient ECG denoising solution suitable for practical biomedical applications.

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Address for correspondence:
Abdulhamed M. Jasim
LE3 5RU
amjj2@Leicester.ac.uk, abdulhamed.jasim@uoninevah.edu.iq